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Artificial neural network analysis of Moroccan solar potential

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ABSTRACT

An artificial neural network (ANN) model is used to forecast the annual and monthly solar irradiation in Morocco. Solar irradiation data are taken from the new Satellite Application Facility on Climate Monitoring (CM-SAF)-PVGIS database. The database represents a total of 12 years of data from 1998 to 2010. In this paper, the data are inferred using an ANN algorithm to establish a forward/reverse correspondence between the longitude, latitude, elevation and solar irradiation. Specifically, for the ANN model, a three-layered, back-propagation standard ANN classifier is considered consisting of three layers: input, hidden and output layer. The learning set consists of the normalised longitude, latitude, elevation and the normalised mean annual and monthly solar irradiation of 41 Moroccan sites. The testing set consists of patterns just represented by the input component, while the output component is left unknown and its value results from the ANN algorithm for that specific input. The results are given in the form of the annual and monthly maps. They indicate that the method could be used by researchers or engineers to provide helpful information for decision makers in terms of sites selection, design and planning of new solar plants.

Contents

1. Introduction

Solar energy is considered as one of the most valuable renewable energy alternative. The exploitation of solar resources is well suited to cope with the limitations of current patterns of energy generation and consumption and to complement existing energy production systems. Solar generation systems can be considered as an attractive option to conventional power generation as well as to enhance sustainable development especially in developing countries like Morocco, which traditionally lacks fossil fuels, but has an important environmental wealth, land availability and great solar potential. Electricity generation using solar technologies has the potential to participate to a country's economic growth, to reduce environmental impacts caused by the use of fossil fuels to generate electricity. Unlike fossil fuels, solar energy does not generate atmospheric contaminants or thermal pollution, thus being attractive to many governments, organisations, and individuals.

Solar power plant planning is founded generally on multi-criteria decision-making processes. So, the selection of appropriate sites should be carried out using multi-criteria planning tools attempting to consider in cooperation, the economic, technical, environmental and social issues. In general, environmental and social criteria are subject to a number of good practice rules relating

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to solar infrastructure installation in accordance with the regional government framework.

However, as electric power demand increases, it will be necessary to evaluate locations for renewable energy generation, consequently, quality and accessibility of solar resource data will enable private investors and public policymakers to access the technical, economical and environmental potential for large-scale investments in solar technologies.

Generally, the data collection of renewable energy resources are made in few meteorological stations particularly in developing countries due to economic restrictions, which may limit the stretch of solar technologies utilisation and development.

Solar resource modelling or mapping is one of the essential management tools for proper development, planning, maintenance scheduling and pricing of solar energy systems [1]. The best exploitation of the solar resources and the optimal operation and sizing of solar power plants may require a detailed knowledge of the solar irradiation characteristics.

Since the design of any cost-effective solar energy system depends on reliable data, therefore, it is always desirable to develop accurate techniques to predict solar irradiation [2]. The various applications of neural networks have been demonstrated in the field of solar energy such as for modelling and design of a solar steam generating plant, for the estimation of a parabolic-trough collector's intercept factor and local concentration ratio, for modelling and performance prediction of solar water heating systems and for heating, ventilating and air-conditioning systems and solar irradiation modelling [2].

ANN approach can provide the basis of an important tool for the solar potential prediction, which might provide helpful information for decision makers in terms of sites selection, design and planning of new future solar plants. ANN is collections of small individual interconnected processing units. Information is passed between these units along interconnections [3]. ANN models may be used as an alternative method in engineering analysis and predictions. They operate like a "black box" model, requiring no detailed information about the system and able to handle large and complex systems with many interrelated parameters [3]. The back-propagation algorithm of the ANN modelling is considered the most suitable method for training multilayer feed-forward networks. Artificial neurons are essentially modelled as multi-input non-linear processes with the weighted interconnections [4].

In the literature, many studies have been focused on providing a forecasting tool in order to predict renewable energy sources and power production with good accuracy. From the wind speed predictions viewpoint, authors in [5–13] have used ANN techniques to forecast the wind speed, the energy output of wind farms and the mapping of wind potential. From the solar irradiation predictions viewpoint, authors in [14–23] have used ANN techniques to assess the solar irradiation, the power produced by a PV generator, hourly values of the diffuse solar irradiation and the solar energy potential. This paper aims to forecast the annual and monthly solar irradiation in Morocco using ANN model. In this paper, data have been inferred using an ANN algorithm to establish a forward/reverse correspondence between the longitude, latitude, elevation and the mean annual and monthly solar irradiation. Specifically, for the ANN model, a three-layered, back-propagation standard ANN classifier has been used consisting of three layers: input, hidden and output layer.

2. Solar irradiation data sources

Estimation of solar irradiation has direct uses in the solar energy received at the earth surface, which represents a fundamental parameter in various disciplines, like climatology, agriculture, building agriculture and solar systems. Unfortunately, measurement networks do not provide solar irradiation data with sufficient spatial and temporal resolutions. For this reason, it is necessary to develop models that are needed to fill spatial and temporal gaps for various regions in the world [24]. Solar radiation is conceptually simple and its attenuation through the atmosphere can be modelled with a fair degree of accuracy [24]. The greatest uncertainty in estimating surface solar radiation is due to the effect of overlying clouds. Satellite observations of reflected solar radiation help to remove this uncertainty, and with the aid of radiation model or correlative relationships they are used to estimate the global distribution of surface radiation [24].

Many models can be used for the estimation of the solar irradiation data from various geographical, meteorological and climatologic variables such as sunshine duration, cloud cover, humidity, temperature, pressure, altitude, etc. Numerous models are available in the literature among them linear models, non-linear models, unrestricted model, power solar radiation model, solar irradiation polygon model, triple solar irradiation estimation model, and fuzzy-genetic solar irradiation models. More details can be found in [24].

Solar irradiation data at the surface of the ground can be obtained by measurements or calculations based on satellite data. Direct measurements of the solar irradiance at ground level can be made with a number of different instruments. Several measurements problem can be encountered, apart failures in the measurement

Table 1
Geographical coordinates of the 41 Moroccan sites.

Code	Site	Longitude	Latitude	Altitude (m)
1	Agadir	9.602	30.396	0
2	Ain bnimathar	2.038	34.012	914
3	Safi	9.245	32.310	14
4	Azilal	6.575	31.971	1331
5	Bouarfa	1.978	32.528	1128
6	Boujdour	14.424	26.136	0
7	Dakhla	15.946	23.700	9
8	El jadida	8.514	33.234	24
9	Errachidia	4.438	31.952	1050
10	Esmara	11.678	26.746	178
11	Essaouira	9.772	31.518	0
12	Fes	5.010	34.034	410
13	Glyab	13.084	21.289	0
14	Imintanout	8.860	31.180	907
15	Kenitra	6.586	34.266	4
16	Khmisset	6.064	33.797	460
17	Khenifra	5.674	32.944	854
18	Khouribga	6.905	32.889	805
19	Laayoune	13.211	27.157	0
20	Lagouira	17.073	21.064	0
21	Larache	6.163	35.183	40
22	Marrakech	8.003	31.634	455
23	Msaysat	15.820	23.161	135
24	Nador	2.944	35.165	29
25	Ouarzazat	6.899	30.921	1133
26	Oujda	1.917	34.696	547
27	Ousard	14.326	22.553	306
28	Ouazane	5.592	34.800	289
29	Chtoukane	14.776	24.637	129
30	Tanger	5.801	35.769	12
31	Tantan	11.113	28.435	48
32	Taounat	4.653	34.538	582
33	Taourirt	2.906	34.420	389
34	Tarfaya	12.931	27.936	3
35	Taroudant	30.468	8.888	232
36	Tata	7.981	29.740	741
37	Taza	4.010	34.225	487
38	Tetouan	5.372	35.577	172
39	Tinghir	5.548	31.533	1314
40	Tiznit	9.741	29.707	231
41	Zagora	5.856	30.335	730

system itself, the sensor may be covered with dirt, frost, or snow, or that the sensor is shadowed by nearby trees or buildings for some of the time during the year. These problems can be removed by careful sitting and maintenance, but it makes it more uncertain to use data where you do not have direct experience with the measurements [25]. In the case of lack or unavailability of direct measurements data, it is possible to estimate the solar irradiation from measurements made nearby. It is also possible to combine data from several different measurement locations to make an estimate for the solar irradiation in a place somewhere between the measurement sites [25].

Numerous methods can be used to estimate the solar irradiation at ground level using data from satellites. Various types of satellites can be used: Geostationary weather satellites take pictures of the Earth at short intervals (every 15 or 30 min) so have a very good time resolution. However, each pixel in the picture typically represents a rectangle of a few km on each side, so the estimate of solar irradiation for each pixel will be the average of such an area. Polar-orbiting satellites fly closer to the Earth, so the space resolution is better. However, they do not stay permanently above a particular area, so they are normally able to take only a couple of pictures a day of a given area [25]. Generally, goodness and quality of satellite-based estimates must be checked by comparison with high quality ground station measurements [25].

3. Renewable energy development in Morocco

Since the beginning of the last decade, Morocco is experiencing a strong economic growth, with an average growth of the GDP around 5% that is driving rapid increases of its energy needs as the annual increase of primary energy demand has averaged 5% and the electricity 7% during the last years [26,27].

However, Morocco is an energy deficient country. In 2010, it imported nearly 97% of its primary energy demand. Its electricity generation capacity was approximately 6405 MW in May 2011 [28]. More than 80% of the electricity produced domestically is from coal, oil and gas. The remainder is from national renewable energy sources (hydro and wind energy) [27]. Against the background of rising energy demand and limited domestic fossil fuel reserves, the use and development of renewable energy technologies have become a major policy incentive in Morocco [29].

Indeed, the country is characterised by an intensive solar irradiation. The annual duration of sunshine hours ranges from 2700 h in the north to over 3500 h in the south, which is equivalent to an average of 5.3 kWh/m^2/day [26].

The wind is also an abundant resource in nearly all the coastal regions [27]. The wind potential is estimated to be more than 25,000 MW. It is estimated that close to 6000 MW will be implemented by 2030 in regions with average wind speeds of up to 9 m/s [26].

Table 2
Monthly solar irradiation data.

Code	Jan (Wh/m^2/day)	Feb (Wh/m^2/day)	Mar (Wh/m^2/day)	Apr (Wh/m^2/day)	May (Wh/m^2/day)	Jun (Wh/m^2/day)
1	3720	4560	5750	6660	7250	7090
2	3060	3920	5370	6510	7340	7800
3	3430	4330	5700	6700	7460	7230
4	3260	4050	5230	6140	6830	6550
5	3370	4330	5700	6980	7490	7740
6	4220	5020	5970	6870	7290	7430
7	4560	5360	6280	7120	7340	7560
8	3310	4240	5690	6700	7580	7140
9	3310	4130	5510	6590	7070	7300
10	4100	4920	5770	6830	7370	7850
11	3650	4500	5830	6830	7670	7030
12	3010	3790	5280	5920	6760	7630
13	4620	5310	6140	6900	7130	7310
14	3510	4310	5440	6560	7240	7410
15	3100	3970	5600	6460	7430	6880
16	3070	3840	5250	5970	6800	6640
17	3070	3820	5080	5950	6720	6500
18	3200	3950	5270	6150	6920	7130
19	3810	4550	5430	6340	6770	7310
20	4830	5660	6460	7180	7230	7530
21	3020	3990	5770	6620	7560	6940
22	3400	4140	5280	6160	6830	7410
23	3980	4700	5450	6190	6430	7740
24	3100	4040	5420	6770	7340	7620
25	3450	4290	5490	6770	7380	7640
26	2930	3780	5130	6290	6990	7690
27	4730	5530	6310	7250	7450	7710
28	2870	3620	5300	5860	6790	7090
29	3830	4560	5360	6210	6510	7830
30	2800	3740	5350	6380	7210	6800
31	3790	4480	5370	6060	6270	6990
32	2790	3400	4900	5740	6570	7260
33	2980	3760	5140	6270	6950	7140
34	4020	4760	5750	6480	6970	6880
35	3430	4230	5350	6280	7000	7260
36	3730	4580	5800	6920	7530	7720
37	2940	3740	5150	5970	6830	7580
38	2750	3510	5030	6030	6830	6570
39	3280	4090	5430	6630	7250	7570
40	3730	4520	5570	6450	6870	7050
41	3600	4440	5770	6820	7350	7480

Since 2009, Morocco is considered having the most ambitious renewable energy programme in the MENA region. In November 2009, the country announced a nine billion dollar programme called the Moroccan Solar Plan, for installing solar energy power plants with a total capacity of 2 GW by 2020. In accordance with the Moroccan Solar Programme, the development of the wind power branch accelerated by speeding up the implementation of the Integrated Moroccan Wind Programme of 2000 MW to be completed by 2020 [28]. By 2020, renewable energy is projected to account for 42% of the 14,580 MW power capacity in Morocco compared to 26% of the 5292 MW capacity in 2008. The total renewable energy production will be equally shared by solar, wind and hydro power [26].

4. Artificial neural network modelling

The Kriging techniques have been adopted for the solar energy predictions, among these Kriging techniques, good results have recently been obtained by the use of ANN techniques [30,31]. In this paper, the data are inferred using an ANN algorithm to establish a forward/reverse correspondence between the longitude, latitude, elevation and the mean annual and monthly solar irradiation. Specifically, for the ANN model, a three-layered, back-propagation standard ANN classifier has been used consisting of three layers: input, hidden and output layer. The ANN input layer consists of 3 units which are associated to the longitude, the latitude and the elevation (linearly normalised between 0 and 1, taking into account, respectively, the maximum and the minimum longitude, latitude and elevation of the territory) of a specific site.

The ANN output layer consists of 1 unit which is associated to the mean annual and monthly solar irradiation available in the location, linearly normalised between 0 (corresponds to the minimum solar irradiation available) and 1 (corresponds to the maximum solar irradiation available). As regards the hidden layer, the choice of the number of units may be subjective since the prediction accuracy on the learning set increases by adding units, but causing a loss of prediction accuracy on new patterns not belonging to the learning set. In this paper, after some testing, a reasonable choice for the hidden layer is 20 units.

In a back-propagation standard ANN learning phase, the characterising "weights" are defined on a given set of patterns. Specifically, the output y_i of each unit i in the network is determined by [12]

$$y_i = \frac{1}{1+e^{-x_i}} \tag{1}$$

This output has a real value between 0 and 1; x_i is the total input to unit i given by [12]

$$x_i = \sum_j w_{i,j} y_j + b_i \tag{2}$$

where w_{ij} is a real number, called weight, representing the strength of the connection from unit j to unit i; the weighted sum of the

Table 3
Monthly and annual solar irradiation data (continue).

Code	Jul (Wh/m^2/day)	Aug (Wh/m^2/day)	Sep (Wh/m^2/day)	Oct (Wh/m^2/day)	Nov (Wh/m^2/day)	Dec (Wh/m^2/day)	Annual (Wh/m^2/day)
1	6620	6180	5460	4160	3800	3340	5440
2	7660	6730	5720	5020	4020	2810	5370
3	7410	6850	5920	4360	3580	3120	5560
4	6250	6490	5550	3950	3120	2950	5290
5	6690	5790	5790	4400	3740	3010	5540
6	7130	6870	6160	5260	4440	3890	5880
7	7170	6870	6240	5620	4840	4230	6090
8	7080	7030	6100	4130	3310	2990	5600
9	7030	6280	5440	4470	3520	2970	5280
10	7880	7000	6010	5470	4660	3730	5840
11	7190	6870	5920	4030	3600	3290	5680
12	7650	6840	5600	4100	3150	2730	5210
13	7990	6620	6040	5510	4850	4220	5950
14	7460	6940	5830	4490	3650	3150	5570
15	7280	7120	5960	4380	3310	2800	5500
16	7030	6860	5600	4140	3200	2770	5240
17	6260	6660	5560	4150	3220	2760	5160
18	7170	6740	5520	4120	3280	2840	5270
19	7510	6470	5670	5400	4410	3520	5430
20	7210	6850	6420	5710	5160	4600	6270
21	6870	7250	6140	3930	3230	2690	5580
22	7310	6550	5350	4550	3780	3010	5250
23	7480	6090	5440	5310	4510	3700	5350
24	7130	7140	6030	4470	3300	2770	5540
25	7530	6470	5650	4980	3870	3160	5480
26	7650	6870	5670	4230	3120	2670	5250
27	7600	6990	6230	5400	4790	4330	6190
28	6630	7080	5700	4040	3020	2600	5220
29	7640	6230	5490	5310	4070	3570	5330
30	6650	7290	5920	4020	3040	2490	5390
31	6590	5730	5420	5200	3940	3440	5070
32	6640	6850	5450	3860	2840	2460	5000
33	6540	6750	5570	4030	3090	2720	5210
34	6910	6530	5970	5150	4220	3660	5570
35	7020	6280	5210	4280	3480	3090	5260
36	7410	6600	5760	4890	3750	3310	5650
37	7310	6690	5480	4050	3040	2650	5140
38	6520	7090	5670	3980	2940	2460	5190
39	7230	6380	5740	4480	3570	3070	5400
40	6820	6320	5470	4580	3730	3730	5370
41	7110	6410	5690	4580	3700	3190	5520

inputs is adjusted by the bias characteristic of the unit i, b_i. Network weights are initially assigned random values uniformly distributed in [−0.3, 0.3]; in each back-propagation cycle, the weights are adjusted in the total output error. The learning ends either after a user-defined number of steps or when the total output error becomes asymptotic, where this error is defined as [12]

$$E=\sum_p\sum_j(O_{p,j}-D_{p,j})^2 \quad (3)$$

where $O_{p,j}$ is the observed output on unit j for learning pattern p and $D_{p,j}$ is the desired output.

The ANN learning procedure is performed on learning set of patterns, where, in our model, each learning pattern p is represented by three parameters (input layer) and by one output parameter (output layer).

5. Results and discussion

5.1. Solar data

In this paper, solar irradiation data of 41 Moroccan sites have been taken from the new Satellite Application Facility on Climate Monitoring (CM-SAF)-PVGIS database [25]. These data were in form of monthly and yearly solar irradiation on horizontal plane (Wh/m^2/day). Table 1 shows the geographical coordinates of the selected sites. The used data are based on calculations from satellite images performed by CM-SAF. The database represents a total of 12 years of data. From the first generation of Meteosat satellites (Meteosat 5–7), known as MFG, there are data from 1998 to 2005 and from the second-generation Meteosat satellites (known as MSG), there are data from June 2006 to May 2010, the spatial resolution is 1.5 arcmin (about 3 km right below the satellite at 0°N, 0°W), the coverage extends from 0°N (equator) to 58°N and from 15°W to 35°E [25].

Tables 2 and 3 display the monthly and annual solar irradiation data. From the analysis of these tables, it can be seen that the mean annual solar irradiation is ranged between 5000 and 6270 Wh/m^2/day which are reached respectively in Lagouira (code 20) and Taounat (code 32). While, the average monthly solar irradiation varies between a maximum of 7990 Wh/m^2/day reached in July (Glayab code (13)) and a minimum of 2460 Wh/m^2/day reached in December (Taounat code (32)). It can be concluded that solar potential of Morocco shows an important variation between all sites in the whole territory, which might be promising for the integration of diverse solar technologies.

Table 4
Predictions of the annual mean solar irradiation obtained by the ANN kriging method learning on 41 sites and testing on the same data.

Code	Site	Annual solar irradiation **(Wh/m^2/day)**	Annual solar irradiation predicted **(Wh/m^2/day)**	Error **(Wh/m^2/day)**	%
1	Agadir	5440	5451	11	0.20
2	Ain bnimathar	5370	5401	31	0.59
3	Safi	5560	5457	103	1.84
4	Azilal	5290	5283	7	0.14
5	Bouarfa	5540	5496	44	0.79
6	Boujdour	5880	5674	206	3.51
7	Dakhla	6090	5852	238	3.91
8	El jadida	5600	5451	149	2.66
9	Errachidia	5280	5306	26	0.49
10	Esmara	5840	5610	230	3.94
11	Essaouira	5680	5581	99	1.75
12	Fes	5210	5168	42	0.80
13	Glyab	5950	5916	34	0.57
14	Imintanout	5570	5452	118	2.13
15	Kenitra	5500	5428	72	1.30
16	Khmisset	5240	5288	48	0.92
17	Khenifra	5160	5210	50	0.97
18	Khouribga	5270	5282	12	0.23
19	Laayoune	5430	5402	28	0.52
20	Lagouira	6230	6218	12	0.19
21	Larache	5580	5463	117	2.10
22	Marrakech	5250	5222	28	0.53
23	Msaysat	5350	5277	73	1.37
24	Nador	5540	5478	62	1.12
25	Ouarzazat	5480	5432	48	0.88
26	Oujda	5250	5218	32	0.60
27	Ousard	6190	5941	249	4.03
28	Ouazane	5220	5263	43	0.83
29	Chtoukane	5330	5279	51	0.96
30	Tanger	5390	5433	43	0.80
31	Tantan	5070	5161	91	1.80
32	Taounat	5030	5162	132	2.62
33	Taourirt	5210	5238	28	0.53
34	Tarfaya	5570	5608	38	0.68
35	Taroudant	5260	5282	22	0.41
36	Tata	5650	5525	125	2.21
37	Taza	5140	5173	33	0.65
38	Tetouan	5190	5165	25	0.48
39	Tinghir	5400	5422	22	0.40
40	Tiznit	5370	5432	62	1.16
41	Zagora	5520	5560	40	0.72
Average				71	1.3

5.2. ANN predictions

In this paper, the learning set consists of the normalised longitude, latitude and elevation and on the normalised average annual and monthly solar irradiation of 41 Moroccan sites. On the other hand, the testing set consists of patterns just represented by the input component (normalised longitude, latitude and elevation), while, according to a classic Jacknife procedure, the output component is left unknown and its value results from the ANN algorithm for that specific input. In the proposed approach, the testing set consists of the same 41 sites. Finally, in order to obtain the annual and the monthly solar irradiation maps on the whole Moroccan territory, predictions are performed on areas of 1×1 km^2 using a digital elevation model (DEM).

Due to the low number of patterns on which the training could be performed, and also due to the rough description of each site (longitude, latitude, and elevation), several tests have been performed in order to produce annual and monthly solar irradiation maps on the whole Moroccan territory. When the ANN was trained on the whole 41 sites on the mean annual solar irradiation data (Table 4), the predictions have shown an average absolute error of 71 Wh/m^2/day which is equivalent to 1.3% on the same sites. The lower error is 7 Wh/m^2/day that correspond to 0.14%. The higher error is 249 Wh/m^2/day that represents 4%, which is however quite low taking into account that the interpolation has been performed on only low number of sites. From these tests, it seemed so worthwhile to produce the annual and monthly solar irradiation maps of the whole Moroccan territory starting from a DEM.

5.3. Annual and monthly solar irradiation maps

Solar potential maps represent a crucial and important task in sites selection and solar power plant design and planning. Starting so from the DEM of Morocco reported in Fig. 1, mean annual and monthly solar irradiation maps of Morocco have been obtained.

Fig. 2 displays the annual solar irradiation map as obtained by ANN technique of the whole Moroccan territory. The predicted annual solar irradiation potential varies between a maximum and a minimum values respectively equal to 6230 and 5030 Wh/m^2/day. This map shows, as it was expected and as it is also widely known from Moroccan decision makers and stakeholders that the most interesting sites for solar power plant installation in Morocco are in the southern, south-eastern and some internal territories. The Mediterranean coast and the southern Atlantic coast seem not be or less important from a solar energy viewpoint, especially for solar thermal applications. But accurate solar data monitoring campaign directly on the site is always highly recommended for a reliable assessment.

Figs. 3–6 show respectively the solar irradiation maps as obtained by ANN technique of Morocco in October, November, December and January. The predicted solar irradiation varies between 3967 and 5668 Wh/m^2/day in October, 2870 and 5100 Wh/m^2/day in November, 2516 and 4536 Wh/m^2/day in December and between 2790 and 4799 Wh/m^2/day in January. These figures reveal a quite similar behaviour. Southern, eastern and some internal regions seem more promising than others and more adequate for intensive solar technology applications, and have a considerable solar potential in that months which can be useful for building efficient peak power control. So, the exploitation of this potential might help in ensuring the energy demand supply.

Figs. 7 and 8 display respectively the solar irradiation maps as obtained by ANN technique of Morocco in February and March. The higher predictions reach 5600 and 6430 Wh/m^2/day, while the lower ones attain 3440 and 4970 Wh/m^2/day respectively in February and March. It can be seen that the south-eastern and some internal regions have a good potential. Whereas, both Mediterranean and Atlantic coasts have a quite important solar potential, which limits the large use of all solar technologies in that coasts.

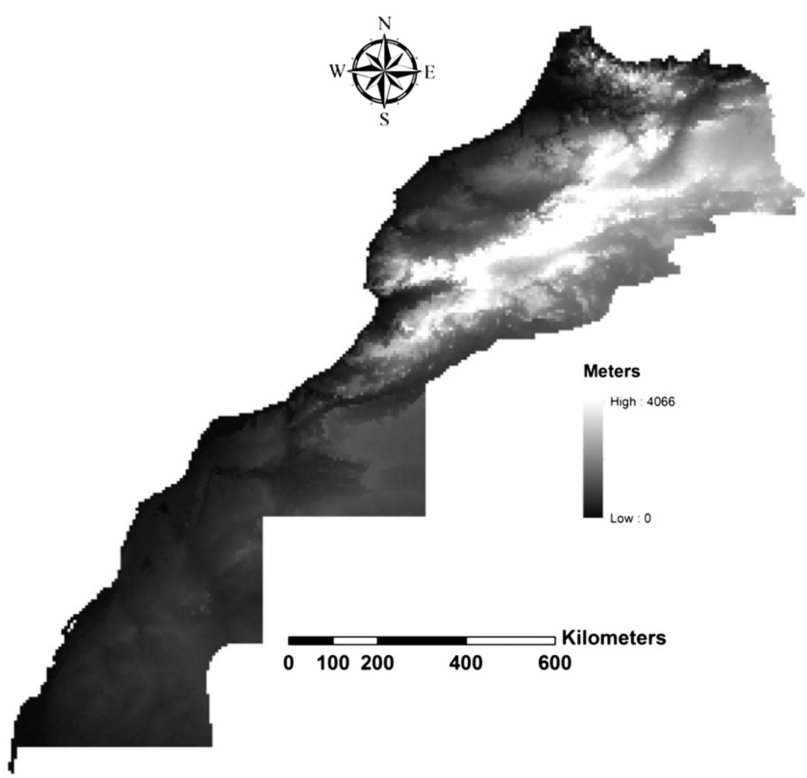

Fig. 1. Digital elevation model of Morocco.

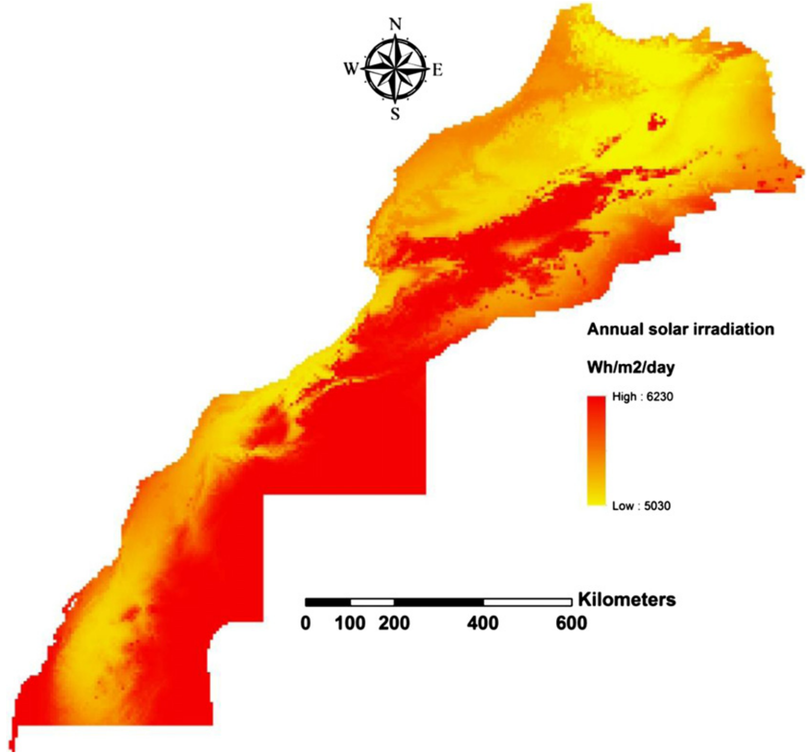

Fig. 2. Annual mean solar irradiation map of Morocco as obtained by the ANN kriging technique.

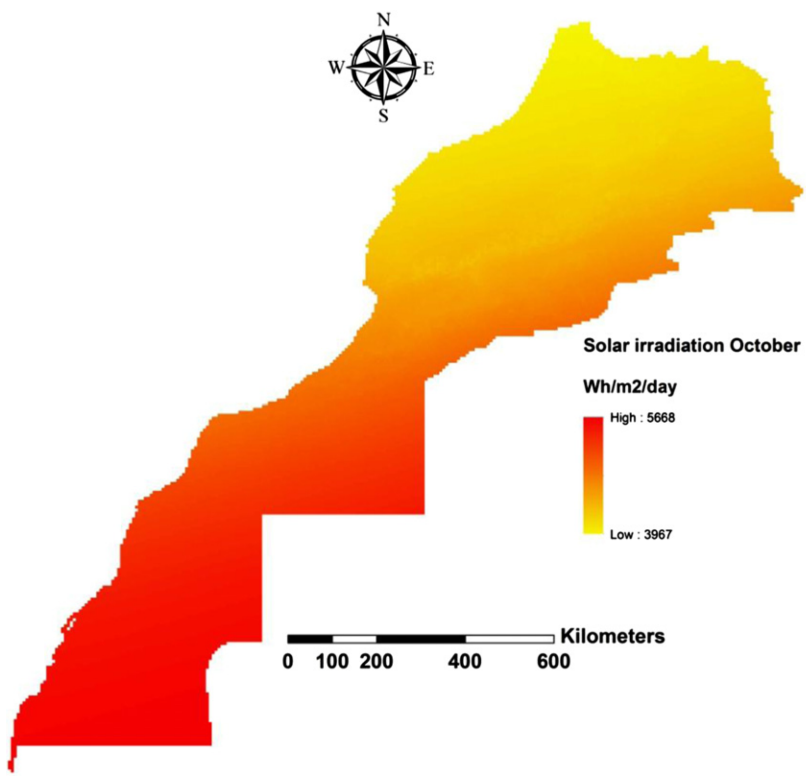

Fig. 3. Solar irradiation map of Morocco (October) as obtained by the ANN kriging technique.

Figs. 9–12 illustrate respectively the solar irradiation maps as obtained by ANN technique of Morocco in April, May, June and July. The analysis of these figures shows that the north-eastern, southern and eastern regions encompass a higher solar potential than internal regions closed to the Atlas mountain and the northern Mediterranean and Atlantic coasts. The predicted solar irradiation varies between 5792 and 7200 Wh/m^2/day in April, 6280 and 7600 Wh/m^2/day in May, 6649 and 7824

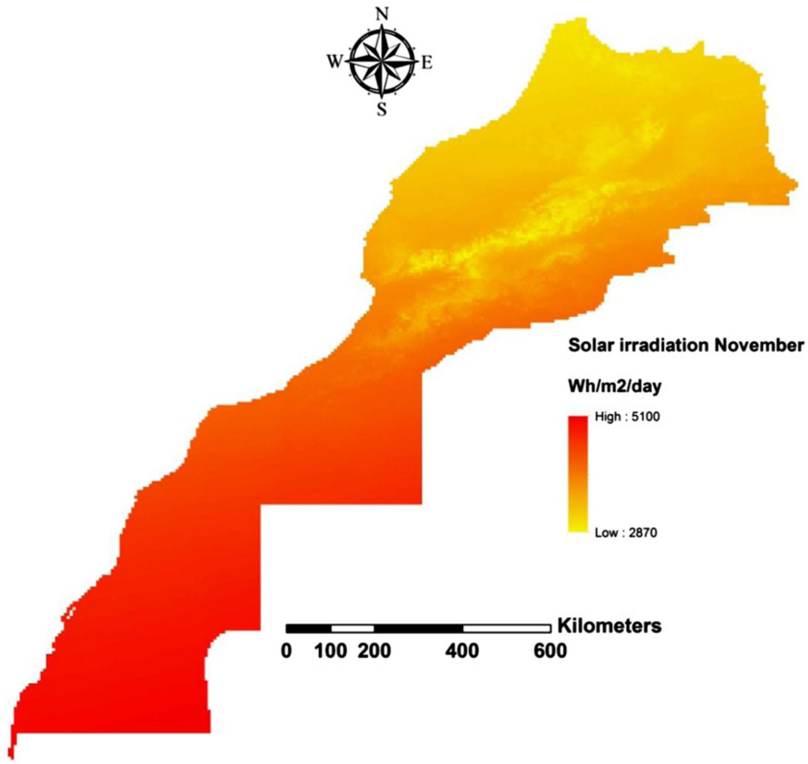

Fig. 4. Solar irradiation map of Morocco (November) as obtained by the ANN kriging technique.

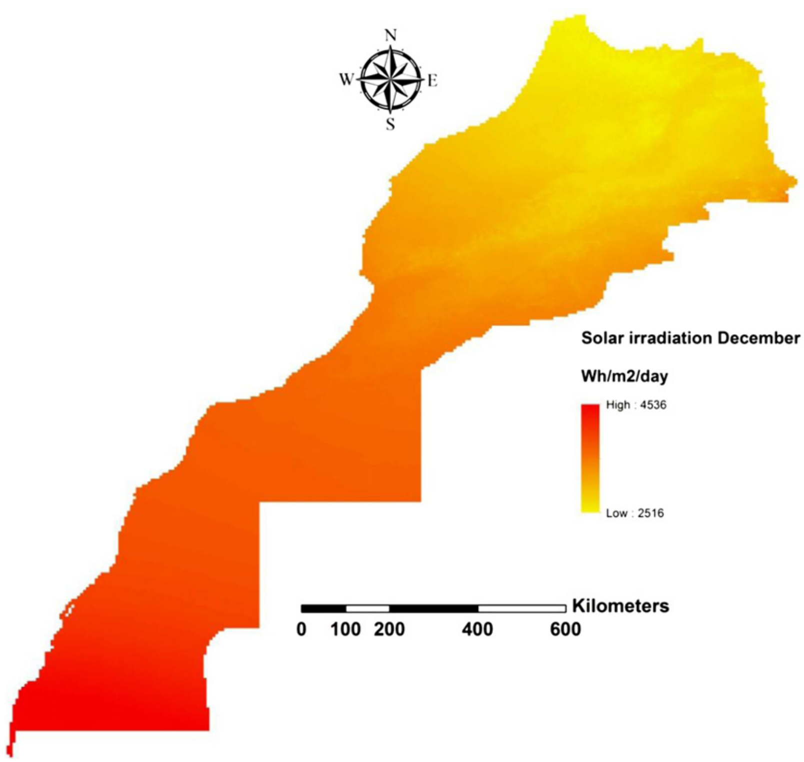

Fig. 5. Solar irradiation map of Morocco (December) as obtained by the ANN kriging technique.

Wh/m^2/day in June and between 6537 and 7710 Wh/m^2/day in July.

Fig. 13 shows the solar irradiation map of Morocco in August as obtained by ANN technique. The predicted solar irradiation ranges between 5768 and 7228 Wh/m^2/day. It can be seen that northern region closed to Mediterranean and Atlantic coasts and southern region exhibit the highest solar potential. The solar irradiation map of Morocco in September as obtained by ANN technique is reported in Fig. 14. It shows that some internal and south-eastern regions are more promising than northern region

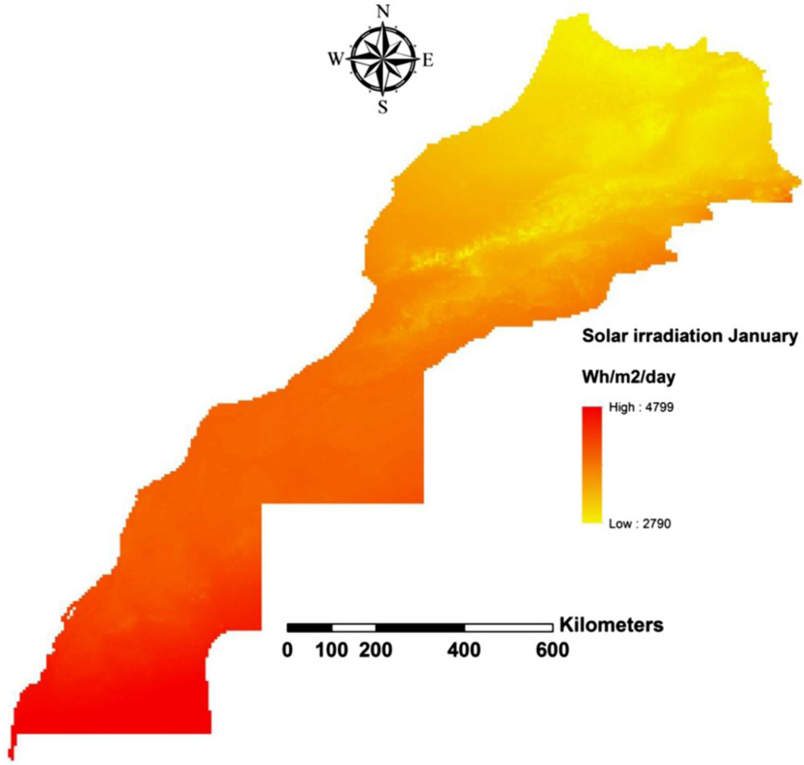

Fig. 6. Solar irradiation map of Morocco (January) as obtained by the ANN kriging technique.

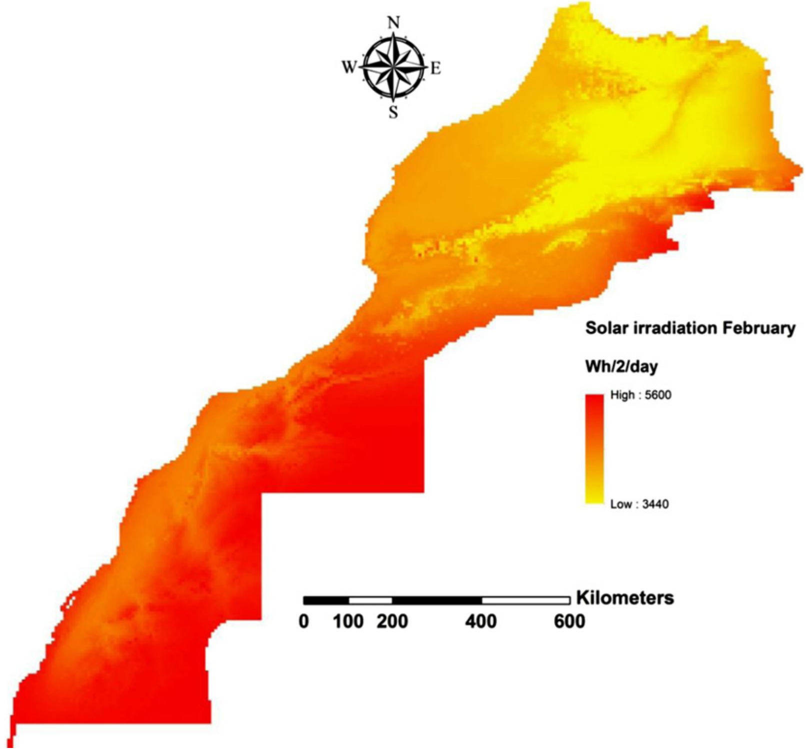

Fig. 7. Solar irradiation map of Morocco (February) as obtained by the ANN kriging technique.

and Mediterranean and Atlantic coasts. The solar irradiation prediction varies between 5310 and 6370 Wh/m^2/day.

The errors between monthly highest and lowest solar irradiation data and prediction are reported in Table 5. It appears that the average error between monthly highest solar irradiation and monthly highest predictions reported in the produced solar maps is equals to 69 Wh/m^2/day which represents 1% of the highest solar irradiation data. The average error between monthly lowest solar irradiation and monthly lowest predictions is equals to 82 Wh/m^2/day which is 1.7% of the lowest solar irradiation data.

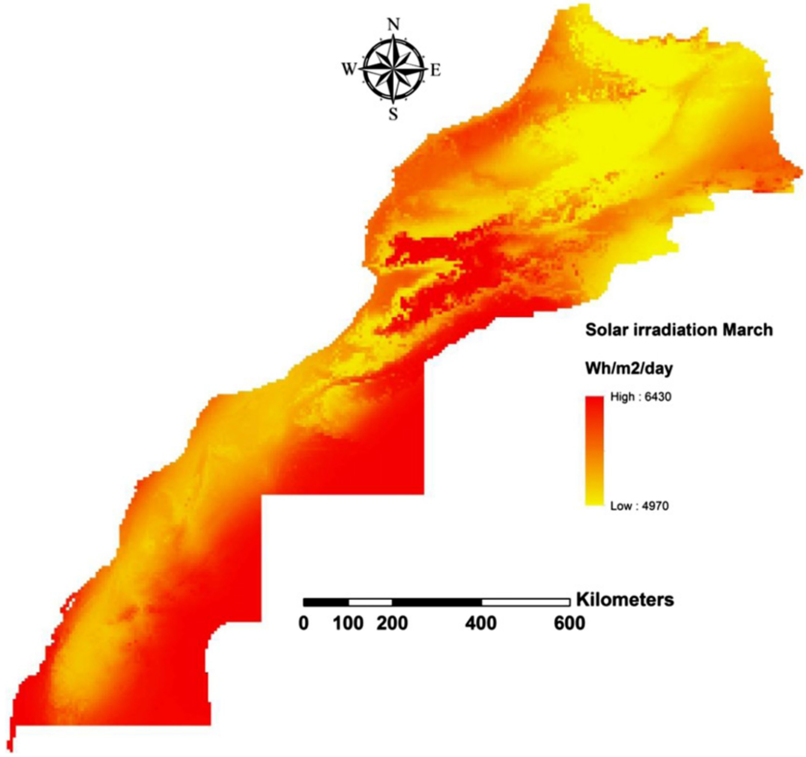

Fig. 8. Solar irradiation map of Morocco (March) as obtained by the ANN kriging technique.

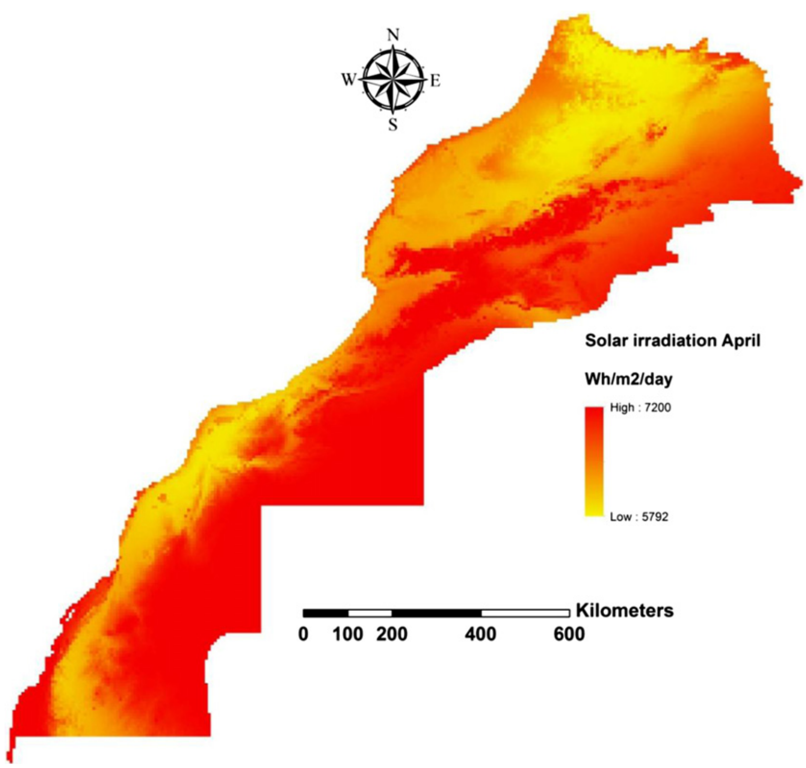

Fig. 9. Solar irradiation map of Morocco (April) as obtained by the ANN kriging technique.

This shows that ANN models are more accurate and versatile to predict solar irradiation.

6. Conclusion

Solar power generation systems can be considered as an attractive option to conventional power generation as well to enhance sustainable development especially in developing countries like Morocco which traditionally lacks fossil fuels, but has an important environmental wealth, land availability and great solar potential. Data have been inferred using an ANN algorithm to establish a forward/reverse correspondence between the longitude, latitude, elevation and the mean annual and monthly solar irradiation. The learning set consists of the normalised longitude,

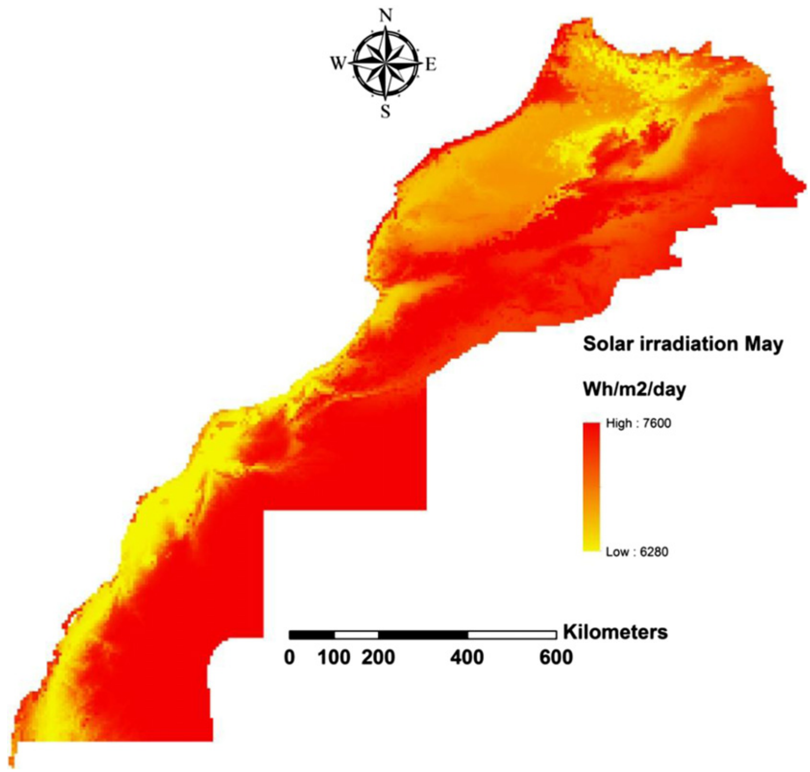

Fig. 10. Solar irradiation map of Morocco (May) as obtained by the ANN kriging technique.

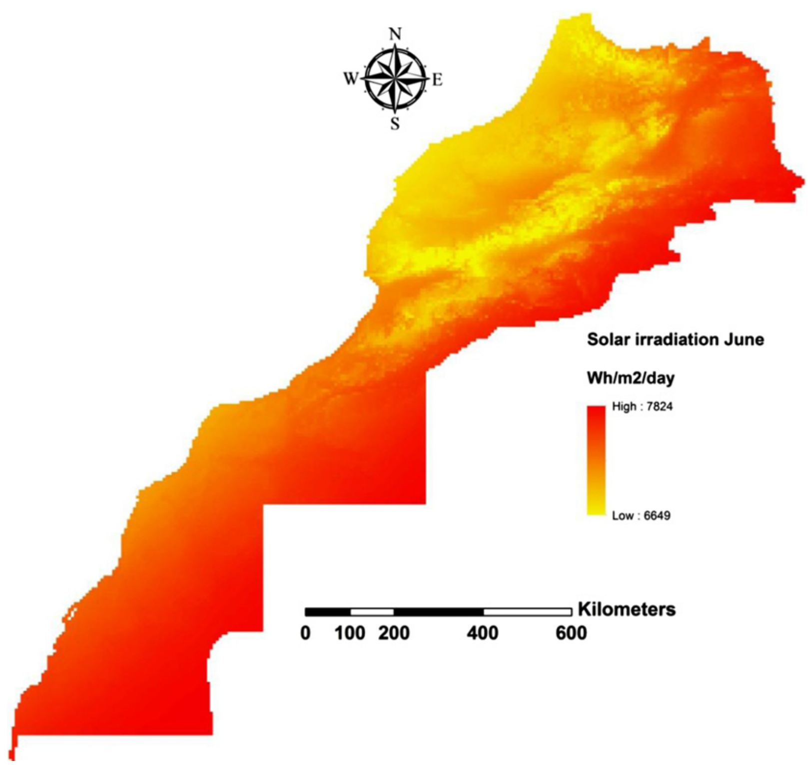

Fig. 11. Solar irradiation map of Morocco (June) as obtained by the ANN kriging technique.

latitude and elevation and on the normalised mean annual and monthly solar irradiation of 41 Moroccan sites. The testing set consists of patterns just represented by the input component (normalised longitude, latitude and elevation), while the output component is left unknown and its value results from the ANN algorithm for that specific input. In our approach, the testing set consists of the same 41 sites. The obtained results indicate that the method could be used by researchers or engineers to provide helpful information for decision makers in terms of sites selection, design and planning of new solar plants. Future research will

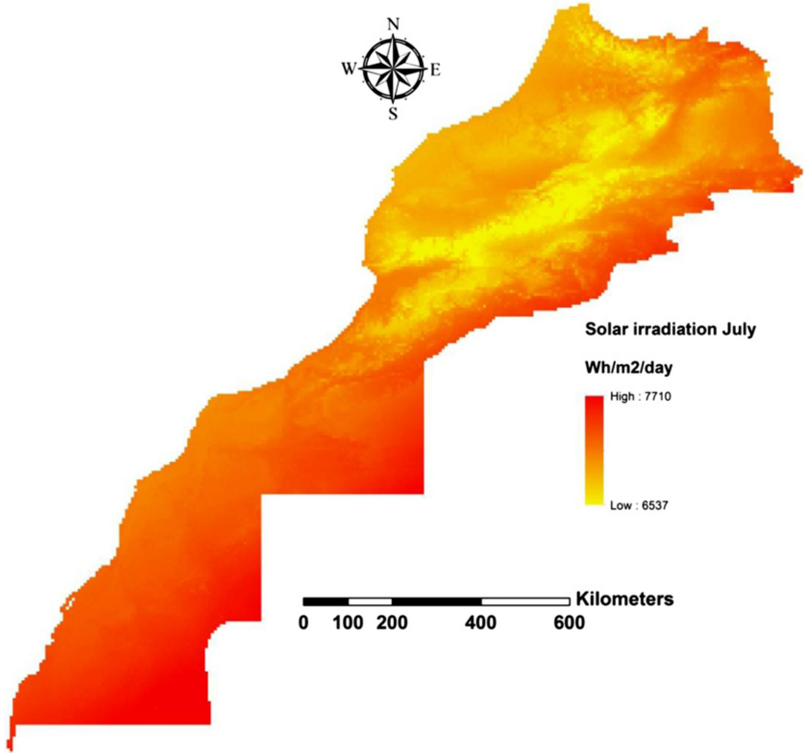

Fig. 12. Solar irradiation map of Morocco (July) as obtained by the ANN kriging technique.

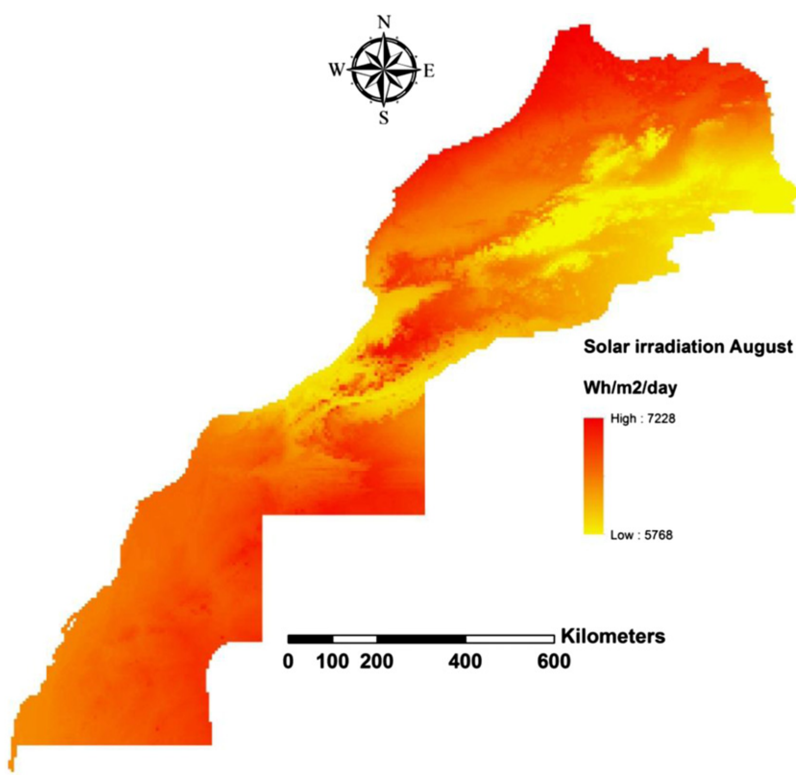

Fig. 13. Solar irradiation map of Morocco (August) as obtained by the ANN kriging technique.

be directed to the selection of the promising sites and the optimal technology to be installed under a multi-criteria approach. In particular, the focus will be dedicated to the design and planning of solar technology infrastructures. The study will concern the development of optimal configurations that may satisfy not only criteria related to the availability of solar resource, but also criteria that seem particular from economic and environmental viewpoints.

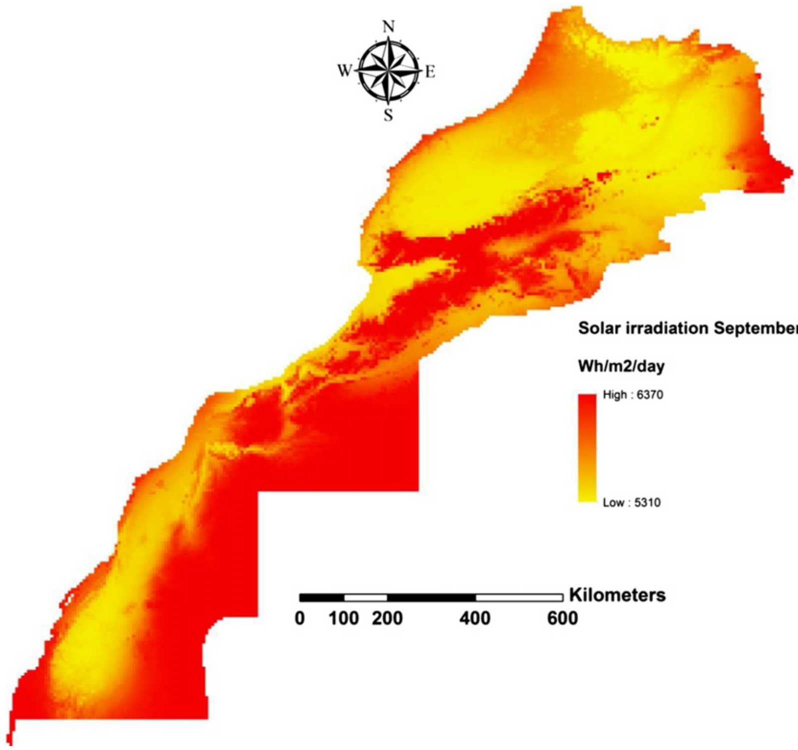

Fig. 14. Solar irradiation map of Morocco (September) as obtained by the ANN kriging technique.

Table 5
Predictions of the monthly mean solar irradiation.

	Highest solar irradiation data **(Wh/m^2/day)**	Highest solar irradiation predictions **(Wh/m^2/day)**	Error **(Wh/m^2/day)**	%	Lowest solar irradiation data **(Wh/m^2/day)**	Lowest solar irradiation predictions **(Wh/m^2/day)**	Error **(Wh/m^2/day)**	%
Jan	4830	4799	31	0.6	2750	2790	40	1.5
Feb	5660	5600	60	1.1	3400	3440	40	1.2
Mar	6460	6430	30	0.5	4900	4970	70	1.4
Apr	7250	7200	50	0.7	5740	5792	52	0.9
May	7670	7600	70	0.9	6270	6280	10	0.2
Jun	7850	7824	26	0.3	6500	6649	149	2.3
Jul	7990	7710	280	3.5	6250	6537	287	4.6
Aug	7290	7228	62	0.9	5730	5768	38	0.7
Sep	6420	6370	50	0.8	5210	5310	100	1.9
Oct	5710	5668	42	0.7	3860	3967	107	2.8
Nov	5160	5100	60	1.2	2840	2870	30	1.1
Dec	4600	4536	64	1.4	2460	2516	56	2.3
	Average		69	1	Average		82	1.7

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